Social Network Analysis: A Survey

Darren Quinn, University of Ulster, UK

Liming Chen, University of Ulster, UK

Maurice Mulvenna, University of Ulster, UK

ABSTRACT

Social Network Analysis is attracting growing attention as social networking sites and their enabled applications transform and impact society. This paper aims to provide a comprehensive review of social network analysis state of the art research and practice. In the paper the authors' first examine social networking and the core concepts and ingredients of social network analysis. Secondly, they review the trend of social networking and related research. The authors' then consider modelling motivations, discussing models in line with tie formation approaches, where connections between nodes are taken into account. The authors' outline data collection approaches along with the common structural properties observed in related literature. They then discuss future directions and the emerging approaches in social network analysis research, notably semantic social networks and social interaction analysis.

Keywords: *Data Collection, Interaction Analysis, Semantics, Social Network Analysis, Social Networking*

1. INTRODUCTION

1. The World Wide Web has brought change to a point where it would be difficult to imagine a world not connected through online networks. In 2010, over 58% of Europe's population of 813 million were internet users (Internet World Stats, 2010), and online social networking sites has emerged as one of the latest innovative applications from the Web, with high-profile sites such as Facebook (http://www.facebook.com) and Myspace (http://www.myspace.com). Their social and economic impact for individuals and business has been described as profound, in the rendering of a new global footprint (Charron et al., 2006). Their usage has evolved from initially being a communication tool towards a content sharing and socialising platform for like-minded people. A diversity of sites have emerged, ranging from the generic social networking sites such as Facebook to specialised content sharing social networks such as Youtube (http://www.youtube.com) and Flickr (http://www.flickr.com), or for specific domains such as ageing users, sites such as Eons (http://www.eons.com) and Sagazone (http://www.sagazone.co.uk).

As such, research of online social networks, which are commonly referred to as Social Network Analysis (SNA), have gained

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increasing attention. SNA intends to model and analyse the interdependent relationships and hidden patterns that make up a social network structure, e.g., friendships, kinships beliefs or interests. Social networks have been studied extensively in multiple disciplines with works in communication (Wasserman & Faust, 1994), anthropology (Barnes, 1972) and sociology (Wellman, 1983). Examples include its application in Epidemiology to understand the spread of disease in a population (Klovdahl, 1985), or in Computing Science to understand the impact of community structures in online social networks (Mislove et al., 2007). The recent emergence of online social networks can be viewed as being the contemporary equivalent of social networks that have traditionally been observed and studied predominantly through the social science of anthropology. As such, research of online SNA is only a recent development, still in its infancy.

Online social networks have many unique characteristics that differentiate them from traditional social networks in terms of formation, evolution and analysis approaches. Firstly, online social networks form and evolve in a bottom-up way with individual users driving, shaping and controlling the networks. Secondly, an individual or group's social network is no longer location restricted, allowing users access to social networks which may previously have been restricted by a particular location or demographic. An enhanced network reach is providing users with greater exposure and visibility to relatable communities and information. Thirdly, online social networks allow for more controlled, directed communications and contact to draw information from specific domains of interest. In addition, contact frequency and information disclosure are self imposed, allowing the user to perform in an observational or contributory role within a network. Given the unique features of online social networks, SNA requires a new wave of approaches and methods different from the approaches traditionally applied in social sciences to gain insights and discover intrinsic regularities. Currently there are a whole raft of SNA approaches being developed, ranging from network modelling, community formation and semantic analysis (Kumpula et al., 2007; Pfeil & Zaphiris, 2009; Erétéo et al., 2009).

As discussed SNA has the potential to be applied to a broad range of areas. The intention of the survey will be to review the area of social network analysis, with particular focus on investigating the impact online social networks have made on the area, discussing past, present and future approaches and their potential application. As part of the survey, a literature review was performed using a variety of techniques which included, searching within the bibliographic databases of Web of Science and Google Scholar with key terms and phrases (e.g., social network analysis, survey). A further review process followed whereby all literature was assessed for suitability within the survey scope. All relevant literature was further classified for inclusion within distinct sub categories and discussed within the appropriate section headings of the survey. The survey remit will not be to discuss areas in specific detail, as has already been achieved in a number of related works and studies, but rather to provide a general insight into common approaches within this broad area. The aim of the paper will be to review the current state of the art of SNA, and to identify and discuss the trends, approaches and technologies of SNA and potential future directions. It will discuss the fundamental areas and related works associated with SNA. The remainder of the paper is organised as follows. Section 2 discusses the trend of social networking sites and their application and trends in related research. Section 3 investigates the motivations of why social networks should be modelled. A range of social network models and their effect on a network structure are further examined. Tie formation and evolution as key network concepts are reviewed. Section 4 focuses on data collection approaches (traditional and contemporary) and discusses common structural properties in understanding the user role in a network, and social network metrics. Section 5 discusses the potential future directions of semantics in online network modelling and analysis. Section 6 summaries the key issues within SNA.

2. BACKGROUND AND CONTEXT FOR SOCIAL NETWORK ANALYSIS

Online social networking has been designed for two primary purposes; (i) to enable the sharing and interaction of data, (ii) to support the social activities of users. Trends in social networking can be seen to have been driven by the advancements in technology, with many of today's popular sites developed after the emergence of web2.0. As a term coined by DiNucci (1999), Web2.0 provided users with a generation of sites which facilitated interactive information sharing, enabling users to become active authors and contributors of content. As an archetypal web2.0 site, Flickr as an example was developed as a photo management site allowing its users to apply semantic meaning through the '*tagging*' of images, a process whereby meta-data is applied to provide context to flat data. With such capabilities, social networking sites are now capable of providing an increasingly enriched and personalised user experience, a key feature which helped fuel the explosion in user popularity, to the point where their impact is accepted as a phenomenon (Cooke & Buckley, 2008; Parameswaran & Whinston, 2007; Kwai Fun, 2008). Facebook as the current number one social networking site (Ebizmba, 2011) was established on the 4th February 2004, and epitomises the rapid growth and success of social networking. In little over 7 years Facebook now has more than 500 million active users, sharing more than 30 billion pieces of content (web links, news stories, blogs, notes, photo albums) each month (Facebook Statistics, 2011). The figures illustrate the popularity of social networking for user connectivity and information sharing. In a short space of time social networking has established itself as a recognised paradigm for communication and interaction. As an example of research carried out in online social networks and their diverse application(s), Facebook has been demonstrated for its use in the sharing of experiences, diagnosis and management of disease (Farmer et al., 2009). Social networking as a communication and interaction tool is providing a connection for isolated individuals or groups wishing to share experiences, events and emotions. The large scale uptake and popularity of such technologies has already generated data sets that are being exploited by both research and industry for the analysis and observation of social networking.

As user popularity has increased in online social networks, so has the associated research interest in a range of disciplines, investigating issues relating to members profiles (Thelwall, 2008; Pfeil & Zaphiris, 2007), information revelation and privacy (Gross et al., 2005), community structures (Lewis et al., 2008; Porter et al., 2009; Traud et al., 2008;), social networking patterns (Pfeil & Zaphiris, 2009; Zaphiris & Sarwar, 2006) and social network modelling (Kumpula et al., 2007; Hunter et al., 2008). In terms of user volume, studies by Chau et al. (2007), Mislove et al. (2007), and Wilson et al. (2009) are noteworthy collecting over 10 million profiles. Mislove (2007), at the time was the largest analysis of online social networks, containing over 11.3 million users and 328 million links. In this work four popular online social networking sites of YouTube, Flickr, LiveJournal (http://www.livejournal.com) and Orkut (http://www.orkut.com) were analysed. The large scale measurement and analysis of structural properties within online social networks confirmed the in-degree and out-degree of users is likely to be equal, and that such online networks contain a heavily connected nucleus of high-degree users; a core connecting to small groups of strongly clustered, low-degree users at the fringes of the network. More recently Wilson et al. (2009) carried out a large scale study on Facebook, analysing more than 10 million user profiles and wall posts to investigate the user interaction patterns across large user groups. Wilson's study is different from previous works in that it moved away from the static analysis of network ties to the dynamic analysis of social interactions on top

Table 1. Social network modelling motivations

1. Social behaviour is complex.
2. Modelling social network structure enables an ability to make inferences about the substructures in a network.
3. To assess the nature of clustering (community structures) in the network.
4. They are useful for complex structures.
5. Assessment of local and global processes.

of static ties, including interaction patterns, evolution, types and weights.

3. SOCIAL NETWORK MODELLING

An online social network can simply be viewed as a structure of individuals, groups or organisations and their respective connections. The individual (group or organisation) within the network is represented as a '*node,*' and the connections between nodes are represented and termed as '*ties.*' Nodes will traditionally form ties through interdependencies such as kinship, friendship or belief etc, and will in most instances be reflective of the sites purpose. For example, the social networking service LinkedIn (http://www.linkedin.com) is designed to link professionals, and the interdependencies between nodes are created on the basis of a professional acquaintance (i.e., industry related). The foundations of any network are built upon a network model and the subsequent tie formation approach, and as such models are the means by which we gain a greater understanding of how networks form and evolve, and enable us to specify the structure of interaction (Toivonen et al., 2009). As discussed by Robins et al. (2007) the modelling of social network structures is driven through five primary motivations (Table 1). Network models and tie formation approaches are discussed for their influence in online social networks.

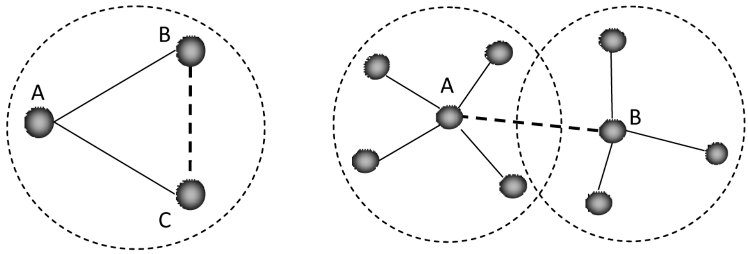
3.1. Models

A host of social network models exists, within the context of online social networks. These models can be classified into three major categories, namely Network Evolution Models (NEM), Network Attribute Models (NAM) and Exponential Random Graph Models (ERGM). Some researchers like Toivonen et al. (2009) further classified the three categories with eight recent network models. In their work social network models were defined within three categorises, however focus was on NEM and NAM. ERGM (also referred to as P* models) were included within this work for comparison purposes only, and will not be discussed within the context of this survey. As a model ERGM is noted as not addressing the network evolution process, a key element when considering dense community structure. NEM's (growing or dynamical) are defined as the addition of links being dependent on the network structure. NAM's (also referred to as spatial models) are defined by the generation of new links being dependent only on nodal attributes (e.g., interest or hobbies). As being representative of the many large scale social networks the formation of community structures is of importance within the overall context of the survey, and it is with this criterion that appropriate models and related literature are further discussed.

Toivonen et al. (2006) presented a model for social networks based on an undirected growing network. The results produced highly connected vertices as a platform for studying sociodynamic phenomena. The approaches used were random attachment, and implicit preferential attachment. The model produced network results that resemble real world social networks, where they retained assorted degree correlations, high clustering, short average path lengths, broad degree distributions and prominent community structures.

In their investigation on the influence of weights, and the formation of community structures, Kumpala et al. (2007) produced

Figure 1. (a) Triadic closure (b) homophily



highly dense community structures through the application of network weights, weights which were based on a coupling in the network structure and interaction strengths. These results are compatible with Granovetter (1973) "The Strength of Weak Ties" hypothesis which states that within a social network, weak ties play a key role in network diffusion. As a network model, community structures emerged only when the strengthening / probability of the assigned weight were at the desired level, taking full account of interaction strength. Fundamentally new ties would only be created preferably through strong ties, and every interaction created thereafter was designed as part of the network model to strengthen the ties.

3.2. Tie Formation Approaches

Network formation and subsequent evolution occurs as nodes form ties, to communicate and share information across the network. Evolution comes about as nodes are added to a network, and ties are established between nodes within the network (e.g., node A joins network and connects to B and C). Attribute databases retain a user's profile, where comparison functions determine a similarity value to other network users. As an example, Facebook uses algorithms to compare and contrast similarity of users. Those nodes deemed to be of a designated probability / weight are then displayed and returned to the user as potential new network tie formations as, "*Friend recommendations.*" The concept of evolution in a social network model is of crucial importance when considering how it defines and affects a networks topology. The two principal network evolution methods Triadic closure and Homophily are discussed below.

Triadic Closure, also referred to as cyclic closure (Kumpula et al., 2007) (Figure 1(a)), was established by Simmel (1908/1950), and subsequently popularised by Granovetter (1973) "Strength of Weak Ties" article. In this instance, tie formation occurs based on the tendency of two friends of an individual to become acquainted. For example, node A is friends with Node B. Node A is also friends with Node C. Triadic closure therefore states that nodes B and C may also become acquainted. Due to its nature such networks, evolve in an outward fashion until the network model is satisfied and this can be through node number constraints within a network.

Homophily (Figure 1(b)) is tie formation occurring based on the tendency for like to interact with like, and associated with the phrase "Birds of a Feather Flock Together" (McPherson et al., 2001). Homophily, in a social network context identifies nodes sharing common characteristics, which have been expressed through their nodal attributes. Two random nodes completely unknown to each other within a network structure can be introduced with a high probability factor due to the similarity of their stated node attributes. For example, node A is male, aged 27, likes soccer, fishing and walking. Node B also likes the same. Homophily therefore states node A and B may become acquainted due to the strength of their similarities. As a concept, it is primarily associated with weighted networks. As an approach, it is em-

Table 2. Example of data collection approaches

Traditional Data Collection	Contemporary Data Collection
Observation Experiments Interviews Archival Records (Diaries) Questionnaires	API (Application Programming Interface) Plug-ins Web Crawlers Online Interviews Online Questionnaires

ployed to structure network ties of various types, most commonly associated with friendship, interest, age, gender, work and marriage etc.

The key difference between the aforementioned approaches is that homophily connections can be established throughout the wider network, whereas triadic closure connections are restricted to within the range of their own sub network. Facebook's "*Find friends*" application tool is an example of a homophily based network, as people connect throughout the wider social network with like minded people sharing similar attributes. As each social network has its designated design and function the appropriateness or suitability of the network formation approach is situation dependent.

4. SOCIAL NETWORK ANALYSIS

SNA can quantify and qualify a social network by analysing and visualising a network, its structure and properties. Analysis usually involves data collection and analysis of relevant structural properties, network metric specification, both of which are described below.

4.1. Data Collection

Data collection methods for SNA have changed considerably over the past two decades. Traditionally data were collected using field observation, simulated experiments and the most used methods of interview and questionnaires (Table 2). Krackhardt and Stern (1988) collected data on the friendships among members of a university class, as part of a study simulating corporations. They applied questionnaires to rate friendships based on a five point scale for their respective class members. Coleman et al. (1966) is a further example of the approach of questionnaires being applied when researching the diffusion of a medical innovation among physicians.

Data collected using such approaches would normally have been stored in physical media and analysed manually. As such these methods required huge amounts of human resources, i.e., researchers to collect and analyse data and subjects to provide information. The process required for traditional data collection is time-consuming, cost-expensive, and context and region dependent, i.e., the results only reflect the patterns or trends of a specific sampling regions or population. This has led to the situation in which data collection became a bottleneck of SNA.

Online social network structures may contain millions of nodes, and the application of traditional data collection methods would in this instance be inefficient and uneconomical both in terms of cost and labour. With the advance and prevalence of Web technologies and online social networking sites, the landscape of SNA has completely changed. Firstly, data acquisition becomes easy as online social networks contain huge user numbers without subject to various constraints of traditional ways, e.g., region and sampling population. Secondly, data collection can be done automatically using crawlers. This gives rise to a number of contemporary approaches (Table 2). These new approaches enable for the remote observation of online social network activity, providing a much less intrusive means of assessing social network structures and dependencies.

Contemporary approaches are now applied as an extremely efficient method for data collection. Facebook API's (Application Programming Interface) are an example of contemporary data collection, whereby software communicates with a remote application over the web through a succession of calls, operated by a web service to provide the network data required. Increasingly the Web is being viewed as an information sharing system, and online social network data collection is now an accepted contemporary solution to the traditional data collection methods. User privacy restricts access to large portions of network data and innovative approaches such as browser plug-in, API's, and web crawlers are routinely applied in contemporary SNA.

Mislove et al. (2007) carried out large scale measurement (11.3 million users, 328 million links) and analysis on online social networks to identify common structural properties. They employed API's and data crawling algorithms as a method of data collection. Common algorithms for crawling graphs include the use of breadth-first (BFS) and depth-first search (DFS). The data collection component accesses through an API with either a BFS or DFS applied dependent upon individual platform restrictions. The methodology employed is statistical sampling, where coverage is approximated, dependent on the number of reachable links.

Data collection in Wilson et al. (2009) overcame Facebook network restrictions through regional network crawls, where access was unauthenticated and opens to all users. A multi-threaded crawler was applied through python, and acquired over 10million users in less than 24 hours. Similar to Mislove et al. (2007), they employed a testing method of repeating crawls for error measurement, achieving a differential of 0.1% for potential missing networks links. As can be seen from existing works, modern approaches provide a means to accurately assess the large scale online social network and their structural properties, overcoming the challenges of time, cost, expense and regional restrictions.

4.2. Structural Properties

Structural properties are measures and metrics that can be used to characterise a social network model. They were proposed and studied by Newman (2003) in his influential research on complex networks and have been used extensively for SNA in the plethora of following research (Mislove et al., 2007; Erétéo et al., 2009; Lewis et al., 2008; Traud et al., 2008; Caverlee & Webb, 2008). By analysing structural properties we can answer questions such as; how compact is a network? Or, how important is a particular node? Due to limited space, we shall only cover the prominent properties of Geodesic, Clustering, Cliques and Centrality to give a general understanding to commonly applied analysis.

Geodesic is concerned with the path length between nodes and is the shortest path between two nodes (Wasserman & Faust, 1994). The distance between two nodes is defined as the length of the geodesic and the average length of geodesic paths provides a measurement used in analysis to describe a networks compactness. As such, Geodesic is applied to determine a measurement of closeness / connectivity in networks.

Clustering is best understood when considering the formation of a community within a social network. It is visualised in network analysis with approaches such as scatter graphs, or through connected graphs such as a dendrogram to give an intuitive representation of dense node formations. With the application of a connected graph as an analysis approach it is important to realise that all points within a network will eventually fuse into a single cluster, and that the number and size of clusters to be indentified is dependent upon the cut-off threshold.

Cliques within a network are defined as "*pockets of high density*" (Scott, 1991). In both a sociological and online context, social relations may in some instances be further divided into cohesive subgroups, producing what is referred to as a clique. Cliques both in the real world and within online social networks are identifiable as groups within groups, with nodes within a subgroup sharing a sub set of values or interests. Cliques in a network are nodes interacting at higher rates in the network, and provide a measure in SNA of community structure (Wasserman & Faust, 1994; Scott, 1991). Cliques form and become recognised as being such within a social network when interactions have been deemed to have reached a desired level of intensity or assessed according to their connectedness.

Centrality is a fundamental social network property, and associated as being the node that is most popular within their particular network sub group. Bavelas (1950) whose primary interests lay in communication networks is acknowledged as an early pioneer in defining the properties of centrality. Nodes of high centrality are extensively involved in relationships with others, a network measurement that assesses the level of influence and connectedness of a node in a network. Related concepts such as betweenness (Freeman, 1979), degree and closeness are extensively used in network analysis (Wasserman & Faust, 1994; Newman, 2003; Hanneman & Riddle, 2005). Closeness centrality is the sum of geodesic distances to all other nodes and the inverse measurement of centrality. Betweenness centrality is the number of times that a node lies along the shortest path between two others nodes. Degree centrality is a count of the number of ties to other nodes in the network and therefore provides a measurement for the level of importance of a particular node in a network.

5. FUTURE DIRECTIONS

While SNA has made substantial progress, existing research has mainly focused on static link analysis, investigating a networks structural property. More recently the direction of research in SNA has begun to change with a range of new directions being explored, some of which are discussed.

Interest is increasing in exploiting the ability of semantic technology to model social networks, networks which contain ties enriched with meaning, and the subsequent data produced. As semantics are defined as being "*the study of meaning in language*" (Crystal, 1991), the semantic web is the rational extension in an online context. Semantic technology enables inferencing and logic to be applied, driven by intelligent agents capable of identifying related information and executing tasks automatically. Since Berners-Lee provided his view which envisioned "*The semantic web will facilitate the development of automated methods for helping users to understand the content produced by those in other scientific disciplines*" (Berners-Lee & Hendler, 2001) the semantic web has come a long way. The impact for online social networks is that technologies are now capable of detecting relationships between objects, enabling an extremely personalised user experience through inferencing and logic. As online social networks have grown in volume and complexity (Golbeck, 2007), there is an increasing interest into the structural and social relationships that are involved on the semantic web (Erétéo et al., 2009; Gruber, 2008; Pfeil, 2007). Semantic technologies have been explored for data modelling, content generation, activity representation, and also for their application in analysing interaction patterns (Chen et al., 2004). Their diverse nature has also seen them investigated as a modelling and representation approach, within ambient assisted living (Chen et al., 2009, Klein et al., 2007; Latfi et al., 2007). As a framework operating within the semantic web, ontologies are a track gaining increasing attention. As a commonly cited definition, an ontology is "*an explicit specification of the conceptualisation of a domain*" (Guarino, 1998). In reality this means that ontologies can be viewed as a set of general reasoning controls operating within the semantic web. With regard to network modelling, ontologies have demonstrated ability to model and mange the social relations of both generic and specific network domains. Models are designed to exploit the power of semantics to support inferencing, reasoning and logic. This is with particular regard to a social networks relational data and user ties (*is a friend of, is* *a relation of, has affiliation to etc*), with the semantic web and social network models now being used to support each other. Semantic modelling using ontology's has been studied and a number of models have been developed such as SIOC (Semantically-Interlinked Online Communities, http://www.sioc-project.org), SKOS (Simple Knowledge Organization System, http://www.w3.org/TR/skos-reference) and FOAF (Friend of a Friend, http://www.foaf-project.org). Network modelling using FOAF is of particular interest due to the relational ties between users in a network. FOAF is designed to represent information about people, and in particular their social connections with three core aspects described; personal information, membership in groups and social connections. FOAF is a subject of research interest, with examples of works including the linking of social networks with FOAF (Goldbeck & Rothstein, 2008), or more recently for video recommendation (Li et al., 2010).

Semantic social network analysis such as that in the work of Ereteo et al. (2009) demonstrates an enhanced ability to exploit social network data through semantic analysis, enhancing the analysis of online social networks. Research in such areas is aimed at gaining a greater understanding into the influence of relations in a network.

When considering the representation of social links through the use of semantic technology, they can be seen to provide rich mechanisms for describing social links. Analysis of social metrics in terms of semantic structures and specifically the typed relationship allow investigations at a deeper level, to gain an enhanced understanding not just of the relationships within networks, but also begin to understand the interactions which occur within these networks and their substructures. Interaction analysis is viewed as an interesting future direction, an approach which can allow a greater understanding to be achieved in determining the impact the social network has for the individual user, allowing for an assessment of key issues such as contact quality. Wilson et al. (2009) questioned "*are social links valid indicators of real user interaction?*" in their investigation of user interaction in social networks. They proposed interaction graphs within this work as a new mode of semantic analysis to quantify user interactions. The findings suggest that social network based sites should be designed with interaction graphs in mind, a method which would better reflect real user activity rather than that of social linkage alone. Interaction analysis of the behavioural differences in Facebook by Quinn et al. (2011) further contributed to the area, demonstrating the approaches ability to understand the use of social network features for each individual user, across young and old age groups. As an approach it involved the investigation of each individual's wall activity, an approach which took full account of a user's interaction history.

6. CONCLUSION

It has been shown that as the internet has grown, so has the development of online social networks. Technologies such as Web2.0, and the increasing use of semantic functionalities changed the user role, with users empowered with authoring capabilities, enabling an enriched personalised experience. User control fuelled adoption rates, to the point where their ensuing social and economic impact is an acknowledged phenomenon. Social networking sites are now an accepted communication tool, connecting users with access throughout the globe for a diverse range of purposes.

Social network models are managing and structuring connections that not too long ago would have remained anonymous. Models have demonstrated their ability in the formation of dense community structures, echoing those of real life, through the use of weighted networks as one example. An enhanced understanding of online social networks is being facilitated through the discipline of SNA, with contemporary data collection methods such as API's defining the structural properties of large scale complex networks. Analysis is now providing an understanding to how user networks form, and evolve. However, more recently the interactions which occur across the networks ties are beginning to be understood in greater detail.

The emergence of online social networks has evolved social network analysis rapidly over the past two decades. Traditional approaches are no longer appropriate for the analysis of large scale online social networks. API's and crawlers as just two approaches that have been applied in a host of recent literature, used successfully to discover the hidden patterns. Structural properties such as clustering and centrality are providing metrics to help understand the complexities that are now being routinely uncovered in related research across a range of areas.

Online social networks present an opportunity to discover and understand the communications of users. While still at infancy, existing limited work on semantic modelling and analysis in this survey highlights the potential to exploit semantic technologies in SNA. However what is of particular interest is the opportunity that may lie within interaction analysis as a new approach, extending traditional social network analysis through the application and observation of semantically enriched technologies, research that may provide a greater understanding of the individual. It can be viewed that we are now at the point where we know all about online networks and their dynamic properties. However, what we are just beginning to understand is the user. Although we know users have adopted this new technology in their millions we know little about the cyber physical impact i.e., how is the merging of the online world affecting the real world, answering questions such as; do such networks positively affect real world communications, if so to what extent? Or can quality of life be enhanced through such technologies. With an increasing array of online networks it is hoped collaboration arrangements can be developed between online networks and research institutes creating new opportunities to understand this phenomenon and their potential.

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Darren Quinn is a PhD research student in the School of Computing and Mathematics, University of Ulster, UK. He has a BSc in Computing and Information Systems from the University of Ulster and has over 10 years experience in industry in a range of positions. His research interests include social computing, gerontechnology and human computer interaction.

Liming Chen is a lecturer at the School of Computing and Mathematics, University of Ulster, UK. He received his BSc and MSc in Computing Engineering from Beijing Institute of Technology, China, and DPhil in Artificial Intelligence from De Montfort University, UK. His current research interests include semantic technologies, knowledge management, intelligent agents, pervasive computing and social computing and their applications in smart homes and intelligent environments. He has published widely in above areas.

Maurice Mulvenna is Professor of Computer Science in the School of Computing and Mathematics at the University of Ulster, UK and a senior member of both the Institute of Electrical and Electronics Engineers and the Association for Computing Machinery. He is also a chartered member of the British Computer Society.